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Unlocking Sustainable Futures: How Digital Economy Transition Drives Urban Low-Carbon Development in China

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Abstract

The digital economy (DE) has become an essential driver of sustainable growth under China's "Dual Carbon" goals of carbon peaking and neutrality. However, limited evidence exists on the DE's city-level effects on green and low-carbon transition. This study investigates the impact and mechanisms through which digital economy transition (DET) influences urban low-carbon development, utilizing panel data from 283 Chinese cities between 2011 and 2018. A comprehensive digital economy development (DED) index is constructed to measure regional digitalization levels. The findings reveal the following: (1) DET significantly improves CEE, and a one-standard-deviation increase in DED raises CEE by approximately 3.7%. (2) The effect of DET on CEE exhibits regional and resource-based heterogeneity, with western regions and resource-dependent cities benefiting more substantially. (3) The mechanisms through which DET improves CEE include stimulating the technological innovation level, attracting foreign direct investment (FDI), and promoting the financial development level. These insights provide valuable theoretical and practical implications for policymakers seeking to harness the digital economy to achieve sustainable urban development and carbon neutrality.

Keywords: digital economy development; carbon emission efficiency; technological innovation; foreign direct investment; financial development; Global Malmquist–Luenberger index

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1. Introduction

Climate change, particularly the greenhouse effect, has emerged as a critical global concern. Carbon dioxide emissions are major contributors to the global carbon cycle and subsequent environmental challenges. Over the past four decades, China has achieved remarkable economic growth. However, this growth has largely been driven by industrial production, resulting in substantial energy consumption and significant carbon emissions [1]. In response, the Chinese government has committed to achieving peak carbon and carbon neutrality—the "Dual Carbon" goals. The integration of digital technologies into production processes, along with the reallocation of resources across sectors such as industry, services, and agriculture, offers new pathways for achieving these targets [2].

A current priority of the Chinese government is to reduce carbon emissions (CE) while maintaining economic growth. In this context, the digital economy (DE) is increasingly regarded as an essential tool for sustaining stable economic development [3]. By leveraging

the DE, the government aims to accelerate technological innovation and optimize industrial restructuring, facilitating a shift from quantitative economic expansion to qualitative growth [4]. The ongoing transition toward a green society, coupled with deepening digital economy development (DED), is exerting a substantial impact across all societal domains and has become a dual engine enhancing high-quality growth in the real economy. The rising market demands and accelerating DE in China further underscore the importance of domestic market needs for spurring local innovation. With clear advantages in industrial scale, technological capability, and platform influence, China's DE is well-positioned for continued expansion. To further amplify the effect of burgeoning domestic demand on local innovation, it is imperative to vigorously advance the DE.

The Chinese government, in promoting modernized governance and enhancing global management capabilities, has accurately identified trends in digitalization, networking, and intelligence worldwide. By implementing strategies such as the Network Power Initiative and Big Data Strategy, along with a series of major policy deployments, China has embarked on a new phase of comprehensive socialist modernization. Aligning with the broader digital transformation of the economy and society, fully unleashing the dividends of digital development will profoundly influence China's high-quality economic development. Technological innovation plays a foundational role in sustaining long-term stable development. The government encourages emission reductions through promoting technological innovation [1], which is crucial for enabling a swift and effective transition from a traditional to a low-carbon economy.

Enhancing carbon emission efficiency (CEE) offers a scientifically sound approach to balancing economic activity and carbon emissions in China. As such, CEE serves as a key indicator for assessing sustainable economic development and emission reduction performance [5]. Significant reductions in carbon emissions and upgrades to the economic structure can be achieved by improving energy efficiency, advancing industrial restructuring, cultivating human capital, and advancing carbon emission storage and reuse technologies [6]. Regarding the relationship between the DE and environmental sustainability, studies indicate that global digitalization could reduce worldwide emissions by 15% [7]. Moreover, digital development can curtail carbon dioxide emissions by enhancing coal utilization efficiency [8]. Advances in Information and Communication Technology (ICT) are also expected to contribute to energy conservation in China through improved energy demand management.

Given this context, a question of widespread academic and policy concern is how to effectively harness the DE to support China's achievement of its Dual Carbon goals. Specifically, does the DE enhance urban CEE in China? If so, what mechanisms underlie this effect? What are the characteristic influences of the DE on carbon emissions? How does this relationship vary across regions? Previous research has explored issues such as the impact of energy structure and the DE on CE [9] and the influence of the DE on haze pollution [10], agricultural carbon intensity [11], and trade-adjusted carbon emissions [7]. Despite the Internet's profound social impact and the DE's growing role in the national economy, it remains unclear whether the DE can simultaneously drive economic development and reduce carbon emissions.

Although previous studies have explored the macro-level relationship between digitalization and environmental outcomes at the provincial or national level, empirical evidence at the city level remains limited. City-level analysis can reveal micro-mechanisms and spatial heterogeneity that provincial aggregates often obscure. This study extends the literature by constructing a city-level digital economy development (DED) index and analyzing its effects on carbon emission efficiency (CEE) across 283 cities in China from 2011 to 2018.

The main contributions of this study are threefold. First, unlike previous studies that measured the DE based solely on Internet development or digital finance [12,13], this research constructs a more comprehensive DED index incorporating both Internet development and digital finance dimensions, using the entropy method to assess the development levels across Chinese cities. Second, this study examines whether the DE can achieve a win–win outcome of economic growth and CE reduction by employing the Global Malmquist–Luenberger (GML) method to measure urban CEE and analyzing the DE's impact. Third, the present investigation further elucidates the mechanisms through which DED influences CEE, focusing on technological innovation investment, foreign investment, and financial development. Finally, we also examine regional and resource-based heterogeneity in the effects of the DE on CEE (Figure 1).

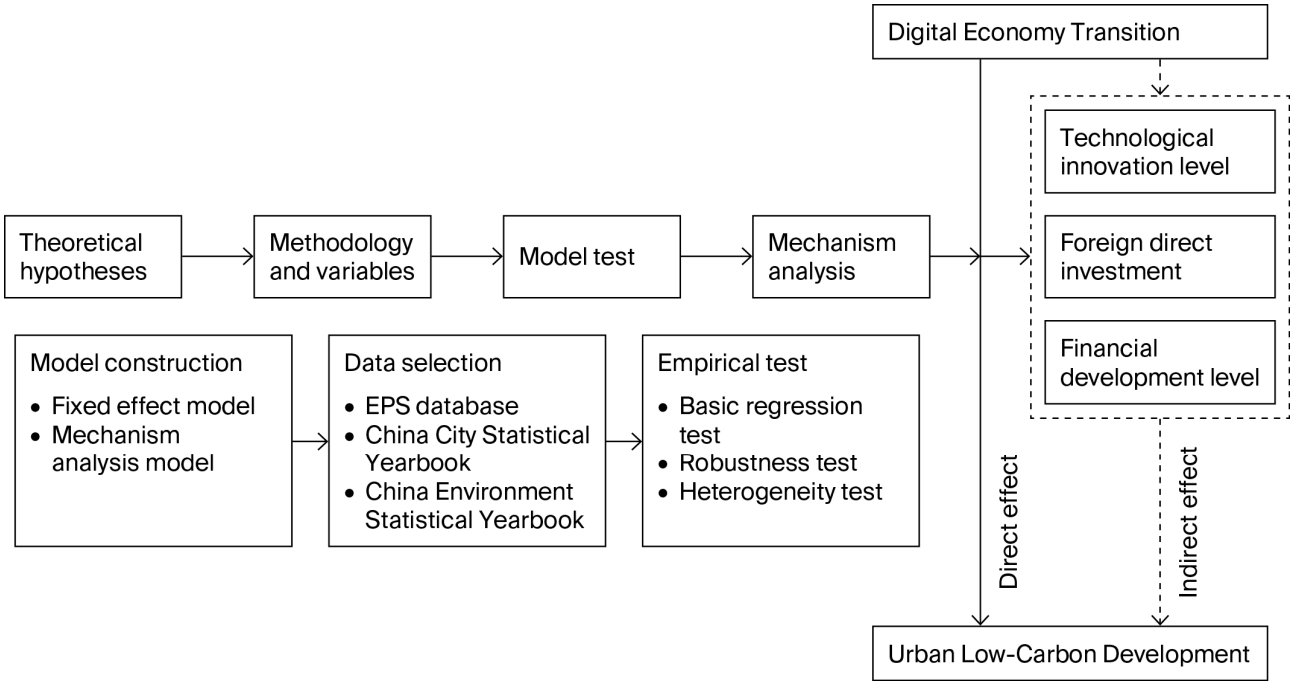


Figure 1. Conceptual framework diagram of the research.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature and proposes the hypotheses; Section 3 describes the variable selection and model construction; Section 4 outlines the empirical strategy and data; Section 5 presents the conclusions; and Section 6 offers policy recommendations.

2. Literature Review and Theoretical Hypotheses

2.1. Literature Review

(1) Research on CEE

The CEE affects the total amount of CE and can be used to determine decreases in CE and economic growth. According to economic development, there is a coupling relationship between economic growth and CE reduction efficiency over the long term, but China's economic development still increases carbon dioxide emissions as a general standard. Additionally, the coupling effect differs between provinces in diverse periods of economic growth over the short term. Short-term coupling is positive in provinces with high development periods and negative in provinces with medium development stages [14]. In general, the carbon dioxide emission reduction efficiency has slightly improved in China, while the efficiency of economic growth presents a downward trend,

with significant divergences between regional efficiency and the decoupling state [15]. Improving CEE is considered to be a readily available avenue to reduce CE [16]. In terms of provinces, China's CEE shows an upswing. From a regional perspective, there are significant differences in the CEE between eastern, central, and western areas, with the highest efficiency of CE observed in the east and the lowest CEE in the west. The CEE is imbalanced in its spatial distribution and hierarchical structure [17]. Researchers have previously found many ways to improve carbon efficiency. Urbanization, for example, can increase the CEE in the middle western areas, with a stronger promoting effect in the western area [18]. Green finance promotes CEE through upgrades to industrial structures and technological advances [17], as do market-driven environmental policies. In a previous study, carbon emission trading policy was found to facilitate the CEE among pilot cities through three mechanisms: technological progress effects, energy consumption structure optimization, and green innovation effects [19].

(2) Research based on DE

In China, the DE is becoming a new driver of technological innovation and economic growth. However, the overall level of China's DE and its high-quality development should still be improved. In addition, the problems of path dependence and lock-in need to be solved [20]. The DE is becoming an increasingly significant element in regional competitiveness each day. The DE in China continues to grow rapidly across the country, as does the degree of DE agglomeration [21]. There is a notable imbalance in regional expansion, with the DE's role in improving high-quality economic growth in eastern, central, and western regions weakening, showing regional heterogeneity [20,21]. Nevertheless, the DE in China continues to develop rapidly, which is mainly attributed to the maturity of digital technology and basic facilities. From a regional point of view, China has a wide regional disparity in the expansion of the DE, with the gap continuing to widen. Ultimately, the DE will enhance the standard of technological innovation, thereby promoting the development of fintech [22]. There are complex spatial interactive spillover effects between environmental pollution and the urban DE in China. The DE is based on using innovative development and green development to curb environmental pollution. Environmental pollution negatively impacts the DE due to policy tightening and the crowding out of talent. As the DE develops rapidly, the coordination between the DE and the environment fluctuates, which could have a profound and lasting influence on sustainable development in the future. When the population and urbanization exceed a threshold value, the DE notably inhibits environmental quality. When the GDP per capita exceeds a certain value, the DE also has a notable influence on environmental quality. The DE affects pollutant emissions mainly through technological and direct effects [23]. The DE acts by improving Green Total Factor Energy Efficiency (GTFEE), actively influencing the improvement of GTFEE by promoting economic development, R&D investments, human capital levels, and urbanization levels. However, as the standard of the DE improves continuously, this phenomenon will promote GTFEE first and then restrain it.

(3) DE and low-carbon development analysis framework

Many scholars have studied the influence of the DE on CE performance from the perspectives of technological innovation [24], industrial production structure [25], and green total factor productivity [26]. Generally speaking, the DE relies on technological innovation to promote the efficiency of the regional green economy. Specifically, the impact of green economic efficiency in the eastern area is greater than that in the central and western areas, and the impact of green economic efficiency in larger cities is greater than that in small cities [24]. There is a U-shaped relationship between the DED and CE of the logistics industry in China. At present, the DE has a notable inhibitory influence

on the CE of the logistics industry, reflecting the first half of this U-shaped correlation. These factors also have significant evolutionary effects [27]. The DE mainly influences regional low-carbon development (RLCD) through environmental governance, upgrades to industrial structures, and technological innovation, becoming a vital driving force for RLCD. The degree of DE decarbonization is significant in the eastern area but not notable in the central and western areas. In addition, DE has made significant contributions to low-carbon development since China launched its carbon emission trading pilot program [28]. The DE of China has notably improved GTFP, albeit with differences between areas. The acceleration effect of the DE on urban GTFP is directly proportional to urban GTFP. Over the long term, the DE has an active influence on China's GTFP. The intermediary transmission of the DE in promoting GTFP is reflected by upgrades to industrial structures [26]. The main way for the DE to promote GTFP is to narrow the technological gap and improve technical efficiency. GTFP and the DE also have nonlinear characteristics. Above a certain threshold value, the DE effectively increases GTFP [29]. The effect of the digital economy on high-quality green development is also positive and nonlinear, but the marginal effect is obviously reduced. This effect primarily relies on industrial structure adjustments and green technology innovations—two intermediary mechanisms. However, digital dividends will be most fully realized in eastern cities, key city clusters, and high-level cities. The digital economy also has an impact on high-quality green development in the surrounding areas through spatial spillover effects [7]. Previous studies have achieved success in the fields of industrial agglomeration, technological progress, industrial structure, renewable energy technological innovation, and foreign direct investment. A few studies also explored the influence of urban DED on CE. Therefore, in this study, we use data from 283 cities to research the influence of China's DED on the CEE of China and its mechanisms.

2.2. Theoretical Hypotheses

Information infrastructure effectively promotes urban greenhouse gas emission efficiency [30]. Information industry innovation can increase the intensity of CE, while the spillovers of technology in cross-industry contexts will continue to abate domestic CE intensity. In addition, digital technology has an influence on CE intensity. Because technology spillovers have a greater impact on emission reductions than technological innovation, digital technologies can promote green development in China [31]. Two-thirds of technological innovations, such as landline phones and broadband subscriptions, increase CE. At the same time, mobile phone users contribute to CE reductions in BRICS countries. High-tech exports, electricity consumption, and technology adoption indicators have also influenced the surge in CE [32]. The coupling effect of green technology and DE inhibits the CEE of surrounding cities to a certain extent but promotes the local CEE [5]. Correspondingly, the DE improves carbon performance by affecting energy consumption and energy intensity. Under diverse levels of energy consumption, energy intensity, and government intervention, the DE has a spatial effect and is nonlinear on CE [28]. As the DE develops, it plays a diminishing role in promoting the decoupling of CE [33], with the influence of the digital economy limiting carbon dioxide emissions. The influence of the digital economy and exports mainly manifests as negative impacts on consumption-based carbon emissions [7]. Ultimately, the DE could serve as a new driver to improve the green development of China and total factor carbon productivity. The effective coefficient of DE on total factor carbon productivity continues to improve but shows an obvious threshold effect of technology accumulation heterogeneity, with the significance standard continuing to increase [34]. Under this background, we propose Hypothesis 1.

Hypothesis 1. *The DE can facilitate urban CEE.*

Technological innovation has a certain drive to facilitate CE performance and achieve green economic development. Industrial upgrading, technological progress, resource allocation optimization, and service sector agglomeration are valid avenues for information infrastructure to promote improved carbon dioxide emission performance [35]. Technological innovation, digital development, and industrial upgrading can reduce CE, improve environmental performance, and facilitate green economic growth [36]. ICT capital can improve CEE mainly by promoting technological advances, improving industrial structure distortion, optimizing resource allocation, and increasing human capital accumulation [37]. From the perspective of areal technological innovation, the mechanism by which the DE drives low-carbon emissions shows spatiotemporal heterogeneity [34]. ICT, financial development, energy consumption, and economic development all increase CE, while the use of renewable energy and international trade reduce CE.

In addition, FDI has an active influence on CEE. Digital infrastructure—such as 5G, the Internet of Things (IoT), and big data centers—has become an important consideration in the site selection of high-end manufacturing and modern service industries. This type of "digitally driven" foreign investment enterprise is usually characterized by higher technological intensity and stricter environmental standards. Through technological spillover effects, demonstration effects, and industrial chain collaboration, such enterprises introduce advanced green production and management technologies into host countries [38], thereby improving overall CEE. The digital economy breaks down information barriers, enabling host-country enterprises to more effectively learn, emulate, and absorb the green technologies of foreign-invested firms.

Finally, the level of financial development also plays an important role in how the digital economy promotes urban emission efficiency [39]. On the one hand, the level of financial development—particularly digital finance—has promoted the growth of the carbon finance market, making the trading of financial instruments such as carbon emission allowances and green bonds more efficient and transparent, thereby providing a direct market-based incentive mechanism for carbon reduction activities [40]. On the other hand, FinTech and digital-inclusive financing help alleviate credit constraints and information asymmetry through electronic KYC (e-KYC), alternative data, and smart contracts, thus improving risk pricing for smaller, innovation-intensive, and green projects.

In summary, DED enhances CEE through both internal and external mechanisms. Internally, DED stimulates technological innovation, improves industrial efficiency, and reduces carbon intensity. Externally, it enhances the quality of FDI and deepens green financial intermediation, thereby reinforcing technological diffusion and capital allocation to low-carbon activities. Under this background, we propose Hypothesis 2.

Hypothesis 2. *The DE can improve CEE through technological innovation, foreign direct investment (FDI), and the financial development level (FDL).*

Resource endowment and geographical region are important factors affecting urban CE. The present energy structure with large coal consumption plays an active part in improving CE. This effect exerts a more significant influence on CE, reflecting resource-based identity. Central China was found to be most affected by this phenomenon and eastern China the least affected. However, as the DE develops, for non-resource-based provinces and eastern regions, the influence of CE caused by the coal energy structure is gradually becoming significantly reduced [9]. For large eastern and resource-based urban cities in China, DED has a notable adverse influence on smog pollution, with a more significant inhibitory effect [41]. Air pollution is characterized by spillover effects and emission aggregation. For central provinces, air pollution from neighboring provinces significantly increases pollution levels. Over the course of its development, China's DE

has had a positive influence on air pollution, especially in the eastern region. The DE has a nonlinear effect on reducing haze, whose mechanism can be verified through the intermediary effect of industrial structure upgrading [10]. Development of the Internet has also played a notable role in improving green economic growth; however, this role gradually increases from east to west, with obvious regional heterogeneity [42]. The effect of carbon reduction governance also varies with the type of city, economic performance, and DE level. Among them, a developed DE, large-scale cities, and a leading economic status have significant emission reduction effects [35]. According to the above research, we propose Hypothesis 3.

Hypothesis 3. *The DE's impacts on CEE exhibit regional heterogeneity.*

A high-level path diagram for the influence mechanism of DED on CE is shown in Figure 2.

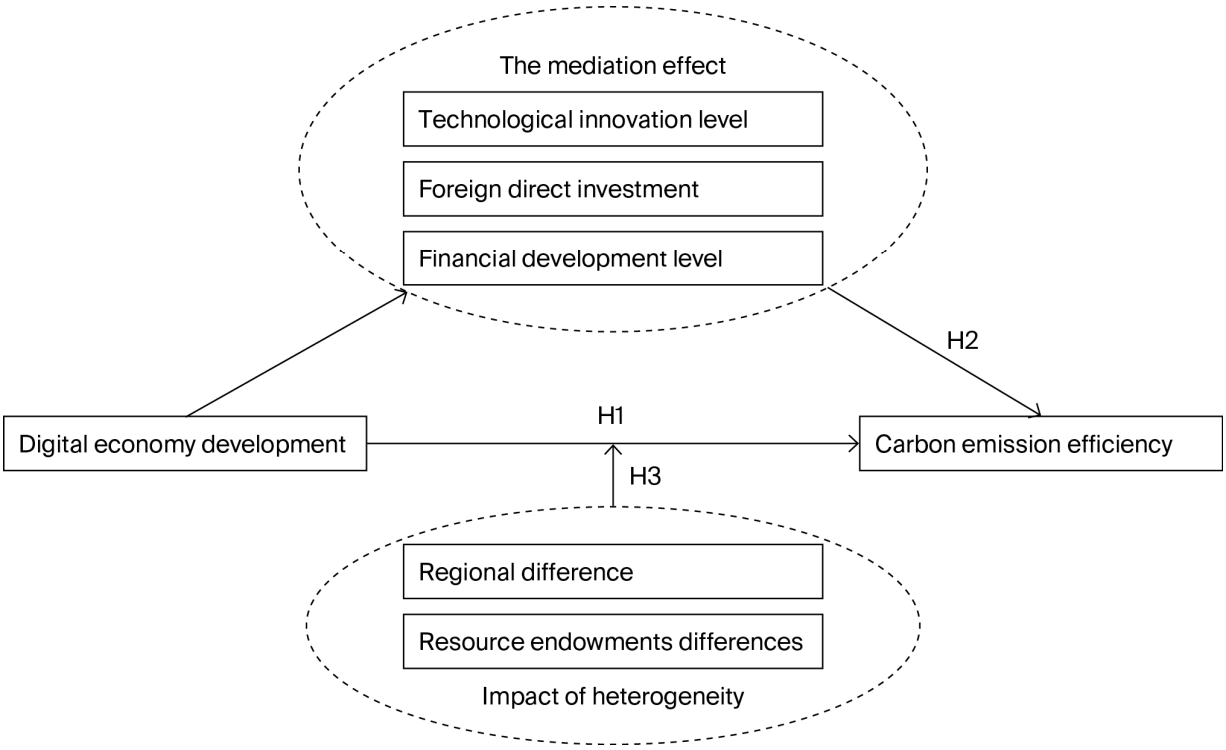


Figure 2. The impact mechanism of DED on CE.

3. Methodology and Variables

3.1. Methodology

3.1.1. SBM-GML Method

To calculate urban CEE scientifically and reasonably, we construct a set of production possibilities containing desirable and undesirable outputs. We also use the SBM-GML index to estimate the CEE of Chinese cities.

Specifically, we assume that each city is taken as the decision-making unit and set as DMUK, where K represents the number of cities. Here, $x = (x_1, \ldots, x_n)$ represents the input of N production factors into each city, where $x \in R_N^+$, M is the desirable outputs obtained, and the desirable outputs are expressed as $y = (y_1, \ldots, y_n) \in R_M^+$. I represents the undesirable outputs, which are rendered as $b = (b_1, \ldots, b_n) \in R_I^+$, t = 1, 2, …. Here, T represents each period of the study, while x^{kt}, y^{kt}, b^{kt} represent the input and output of

cities at this stage. The production possibility set measured by the DEA method can be shown as follows:

$$P^t(x) = \left\{ \begin{array}{c} (y^t, b^t) : \sum\limits_{k=1}^{K} z_k^t y_{km}^t \geq y_{km}^t, \ \forall m; \ \sum\limits_{k=1}^{K} z_k^t b_{ki}^t = b_{ki}^t, \ \forall i; \\ \sum\limits_{k=1}^{K} z_k^t x_{kn}^t \leq x_{kn}^t, \ \forall n; \ \sum\limits_{k=1}^{K} z_k^t = 1, z_k^t \geq 0, \forall k \end{array} \right\} \tag{1}$$

where z_k^t represents the weight of observed values in each city. However, the possible set of production technology measured using this method does not take into account the reference of non-contemporaneous technology, which may introduce backward production technology into the $P^t(x)$ model. To avoid this situation, we refer to the existing method and build a global production possibility set $P^G(x)$ based on $P^t(x)$, thus making the production frontier consistent and comparable. The specific model is constructed as follows:

$$P^G(x) = \left\{ \begin{array}{c} (y^t, b^t) : \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} z_k^t y_{km}^t \geq y_{km}^t, \ \forall m; \ \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} z_k^t b_{ki}^t = b_{ki}^t, \ \forall i; \\ \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} z_k^t x_{kn}^t \leq x_{kn}^t, \ \forall n; \ \sum\limits_{t=1}^{T} \sum\limits_{k=1}^{K} z_k^t = 1, z_k^t \geq 0, \forall k \end{array} \right\} \tag{2}$$

Traditional radial DEA cannot measure the efficiency problem with unexpected outputs. The non-radial and non-angular SBM directional distance function used in this study effectively overcomes the relaxation problem in the efficiency evaluation. On this basis, we define the global SBM directional distance function with undesirable output efficiency as follows:

$$\vec{S_V^t}(x^{t,k}, y^{t,k}, b^{t,k}, g^x, g^y, g^b) = \max_{s^x, s^y, s^b} \frac{\frac{1}{N}\sum_{n=1}^{N} \frac{S_n^x}{g_n^x} + \frac{1}{M+I}\left(\sum_{m=1}^{M} \frac{S_m^x}{g_m^x} + \sum_{i=1}^{I} \frac{S_i^b}{g_i^b}\right)}{2} \tag{3}$$

$$s.t. \sum_{k=1}^{K} z_k^t x_{kn}^t + s_n^x = x_{k'n}^t, \ \forall n; \ \sum_{k=1}^{K} z_k^t y_{km}^t - s_m^y = y_{k'm}^t, \forall m; \sum_{k=1}^{K} z_k^t b_{ki}^t + s_i^b = b_{k'i}^t, \forall i;$$

$$\sum_{k=1}^{K} z_k^t = 1, z_k^t \geq 0, \ \forall k; \ s_m^y \geq 0, \ \forall m; \ s_i^b \geq 0, \ \forall i$$

where g^x stands for the direction vector of input reduction, g^y stands for the direction vector of increases in desirable output, and g^b represents the direction vector of reductions in undesirable output. s_n^x stands for the input redundant slack vector, s_m^y represents the expected output insufficient slack vector, and s_i^b represents the undesirable output excessive slack vector.

In this study, the Global distance function SBM is used to construct the global-Malmquist–Luenberger (GML) index, thereby overcoming the limitations of the Malmquist–Luenberger (ML) index, which often has no feasible solution when solving linear programming. Additionally, the GML index can avoid the front facing inward deviation of ML index production, effectively avoiding the problem of "technology regression". In addition, the GML index is further subdivided into technical efficiency (Geffch) and technical progress (Gtech) indexes. The specific model construction is as follows:

$$GML_t^{t+1} = \frac{1 + \vec{S_V^G}\left(x^t, y^t, b^t; g^x, g^y, g^b\right)}{1 + \vec{S_V^G}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^x, g^y, g^b\right)} = geffch_t^{t+1} \times gtech_t^{t+1} \tag{4}$$

$$geffch_t^{t+1} = \frac{1+\vec{S}_V^t\left(x^t, y^t, b^t; g^x, g^y, g^b\right)}{1+\vec{S}_V^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^x, g^y, g^b\right)} \tag{5}$$

$$gtech_t^{t+1} = \frac{\left[1+\vec{S}_V^G\left(x^t, y^t, b^t; g^x, g^y, g^b\right)\right] / \left[1+\vec{S}_V^t\left(x^t, y^t, b^t; g^x, g^y, g^b\right)\right]}{\left[1+\vec{S}_V^G\left(x^{t+1}, y^{t+1}, b^{t+1}; g^x, g^y, g^b\right)\right] / \left[1+\vec{S}_V^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g^x, g^y, g^b\right)\right]} \tag{6}$$

where the index represents the relative change value of urban CEE between t period and t+1 period, and $\vec{S}_V^t\left(x^t, y^t, b^t; g^x, g^y, g^b\right)$ and $\vec{S}_V^G\left(x^t, y^t, b^t; g^x, g^y, g^b\right)$ represent the current and global SBM distance functions, respectively. Therefore, we adopted the GML index to represent the CEE of Chinese cities, as follows:

1. GML > 0 represents an improvement in the CEE of Chinese cities compared with the previous period;
2. GML < 0 represents a decrease in the CEE of Chinese cities compared with the previous stage;
3. GML = 0 indicates no change in the CEE of Chinese cities.

3.1.2. Benchmark Model

To explore the impact of DED on the CEE (considering the availability of data, the heterogeneity of prefecture-level cities, and missing variables), the benchmark model set in this paper is as follows:

$$\mathrm{CEE}_{it} = \alpha_0 + \alpha_1 DED_{it} + \alpha_2 Control_{it} + Pro_i + Year_t + Pro_i * Year_t + \varepsilon_{it} \tag{7}$$

where i and t stand for the city and year, respectively; CEE_{it} is the explained variable representing CEE; DED_{it} is the core explanatory variable representing DED; and $Control_{it}$ is the control variable matrix. In addition, because the CEE differs greatly between different regions, we also control the individual effects of the province and time, namely Pro_i and $Year_t$. Here, α_1 and α_2 are the regression coefficients of the core explanatory and control variables, respectively, and ε_{it} stands for a disturbance term.

3.1.3. Mechanism Analysis Model

Based on theoretical analysis, DED can indirectly affect the CEE of prefecture-level cities in three ways: technological innovation level (TIL), foreign direct investment (FDI), and financial development level (FDL). The present research uses the following model to test Hypothesis 2. The specific model is constructed as follows:

$$M_{it} = \beta_0 + \beta_1 DED_{it} + \beta_2 Control_{it} + Pro_i + Year_t + Pro_i * Year_t + \varepsilon_{it} \tag{8}$$

where M_{it} represent the regional level of TIL, FDI, and FDL, respectively, which are all the mechanism variables. All other settings are the same as those in Equation (8).

3.2. Variable and Definition

3.2.1. Independent Variable

Digital economy development (DED): The measurement scale of the existing literature on the DE is mainly limited to the national and provincial level, with few studies employing a measurement scale at the city level [5]. From the two perspectives of Internet development and digital finance development, we measure the urban DED (see Table 1). Specifically, in terms of Internet development, we use the four dimensions of Internet penetration rate, Internet practitioners, Internet-related output, and Internet users to measure the degree of

Internet development. To study digital finance development, we adopt the Index of China digital Inclusive finance jointly compiled by Peking University Digital Finance Research Center and Ant Financial Group. In addition, the development index of DE is calculated using the entropy weight method, denoted as DED.

Table 1. DED evaluation index system.

The Target Layer	Criterion Layer	Variable Definitions
The digital economy development index	Internet penetration rate	Internet Users per 100 persons (persons/100 persons)
	Internet employees	Percentage of Employees in Computer Services and software (%)
	Internet-related output	Total telecom business per capita (CNY/person)
	Internet users	Number of mobile Phone Users per 100 Persons (persons/100 persons)
	development of digital finance	China Digital Financial Inclusion Index (-)

3.2.2. Explanatory Variable

Carbon emission efficiency (CEE). When evaluating CEE, the frontier of each period is considered to be independent of each period. Thus, we consider the SBM directional distance function of unanticipated outputs and use the GML index to measure CEE. The input indicators include labor force (LF), capital stock (CS), and energy consumption (EC). Meanwhile, we apply the actual GDP as the desired output indicator and the CE as undesired output. CE in cities is calculated based on the consumption of all fossil energy combined with the CE factor of energy types from the energy statistical yearbook of each city [43].

3.2.3. Mechanism Analysis Variables

Technological innovation level (TIL). As a key enabler of cities' low-carbon transition, the digital economy (DE) increases technological innovation. This higher innovation then improves carbon-emission efficiency through cleaner production, process optimization, and green technology adoption. The urban DED can drive regional economic vitality, affording local governments more funds to invest in urban scientific research and development. Because of the negative externality of CE reduction, government technology input is an important measure to encourage enterprises to invest in low-carbon technology R&D. In the meantime, the government often adopts subsidies, tax reductions, and other means to encourage enterprises to carry out technological innovation, thereby facilitating the low-carbon development of cities [44]. Therefore, we proxy the level of urban technological innovation with government technology input, defined as the share of science-and-technology-related fiscal expenditures in local GDP.

Financial development level (FDL). The rapid development of the financial industry, especially the development of green finance, is a significant driving force facilitating green innovation and realizing green and low-carbon development [45]. The rapid development of DE has also promoted the rapid development of China's financial system. Indeed, financial loans, green credit, and other methods to assist enterprises in CEE are very important. Therefore, we adopt the ratio of the loan balance of financial institutions to the regional GDP to represent FDL.

Foreign direct investment (FDI). The pollution halo hypothesis proposes that foreign direct investment can introduce green and low-carbon technologies and advanced management experience to the local area, thus promoting the green and low-carbon development of a city. The development of DE is also conducive to improving the urban economy and environmental levels, thereby attracting more foreign investments [46]. Therefore, to

explore the intermediary role of FDI between DED and urban CEE, FDI is logarithmically represented as the amount of foreign capital utilized.

3.2.4. Control Variables

To control the effects of other factors on CEE, we apply the following control variables: Economic development (ED): The level of regional economic development is expressed by GDP per capita. Industrial structure (IS): Upgrading the industrial structure is key to reducing urban CE [47]. The level of industrial structure is represented by the proportion of the output value of the secondary industry in regional GDP. Government intervention (GI): Local governments implement industrial policies to adjust the industrial structure for performance appraisal, which supports resource utilization efficiency, thereby alleviating environmental pollution and reducing the CE in cities. GI is expressed as the proportion of public financial expenditures in regional GDP. Population density (PD): Population density is one of the important factors affecting urban CE. Here, we use the ratio of urban permanent population to the area of the city to represent urban PD (see Table 2).

Table 2. Variables' definitions.

Variable Classification	Variable Symbol	Variable Definitions
Explained variable	CEE	Comprehensive index measurement
Explanatory variable	DED	Comprehensive index measurement
Mechanism analysis	FDI	The logarithm of the amount of foreign capital actually utilized
	TIL	The proportion of science and technology investment in public finance expenditure
	FDL	The proportion of the loan balance of financial institutions in the regional GDP
Control variables	ED	The logarithm of region per capita GDP
	IS	The proportion of the output value of the secondary industry in regional GDP
	GI	The proportion of public finance expenditure in regional GDP
	PD	The proportion of permanent urban population in the area of the city

3.3. Data and Descriptive Statistics

Based on the panel data of 283 prefecture-level cities in China from 2011 to 2018, we empirically analyzed the impact and mechanism of DEE on China's low-carbon development. All data for relevant indicators were mainly collected from the China City Statistical Yearbook, China Environmental Statistical Yearbook, and China Digital Inclusive Finance Index from 2011 to 2018. To ensure data continuity and accuracy, the missing values were supplemented using interpolation methods. Table 3 presents the descriptive statistical analysis of the specific variables used in this study.

Table 3. Descriptive statistics.

Variable	N	Mean	St. Dev	Min	Max
CEE	2248	1.020	0.304	0.154	5.644
DED	2248	0.091	0.093	0.008	0.882
ED	2248	10.697	0.594	8.773	15.675
IS	2248	0.479	0.105	0.136	0.893
GI	2248	0.196	0.101	0.000	0.916
PD	2248	438.346	341.554	9.787	2648.256
TIL	2248	0.016	0.016	0.000	0.207
FDI	2248	11.316	3.324	0.000	16.878
FDL	2248	0.954	0.582	0.000	7.450

4. Empirical Results and Discussion

4.1. Spatial Characteristics of Carbon Emission Efficiency

Using the GML method, we estimated the CEE of 283 cities in China from 2011 to 2018. The spatial characteristic maps of CEE in 2012, 2015, and 2018 are presented in Figure 2. Using these data, we preliminarily analyzed the spatial characteristics and distribution of CEE. In 2012, the CEE of prefecture-level cities in China was not high overall, with only some prefecture-level cities presenting high CEE values. The CEE in most cities remained low, with an obvious lack of balance in general cities. In 2015, the CEE of prefecture-level cities did not significantly improve in China, but regional changes occurred. Thus, the areas with high CEE became areas with low CEE, and some areas with low CEE presented an increase in CEE. In 2018, the CEE of prefecture-level cities in China improved overall, while the CEE in a few areas remained unchanged. Meanwhile, based on the data published by the China Academy of Information and Communications, the scale of China's DE is on the rise, increasing from CNY 9.5 trillion in 2011 to CNY 39.2 trillion in 2020. The ratio of DE in GDP is also on the rise, reaching 38.6% in 2020, with an increase of 9.7%, which is much higher than the GDP growth during the corresponding period. These results suggest that growth of the DE may have had a particular influence on the CEE of cities. Subsequently, we further verify our conclusions using additional empirical evidence (Figure 3).

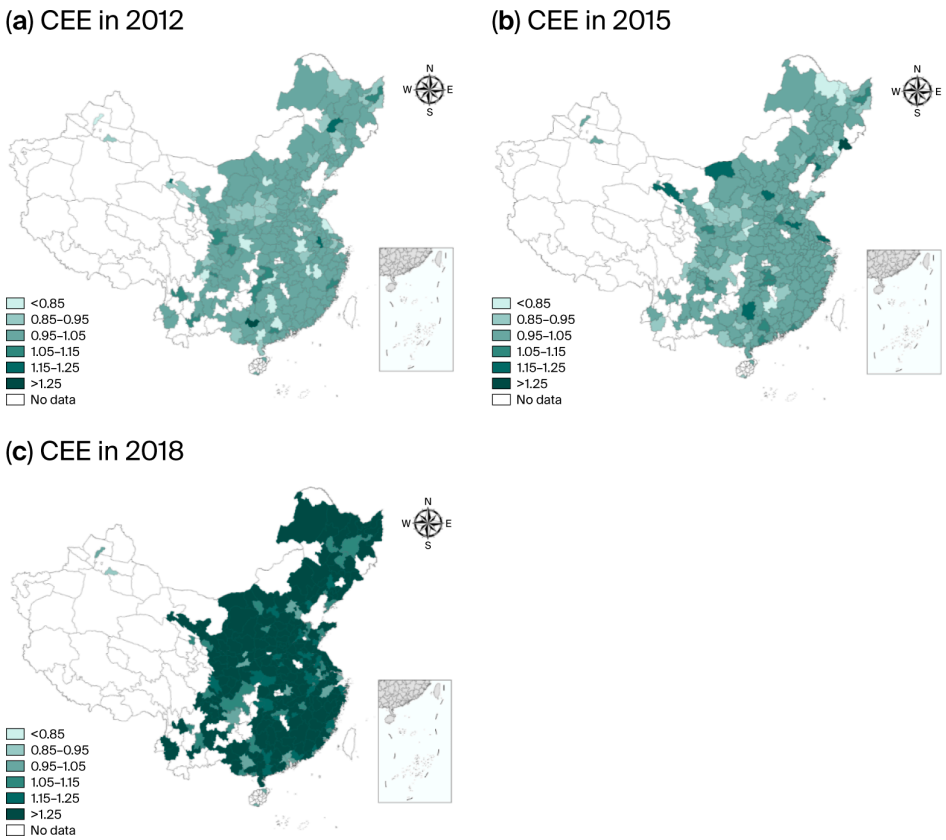


Figure 3. Evolution process of CEE in prefecture-level cities in China.

4.2. Basic Model Regression Results

Table 4 reports the benchmark regression results, where CEE is the explained variable. Because the carbon emission process varies with time and regional heterogeneity, a two-way fixed-effects model is employed as the standard estimation approach. Column (1) presents the estimation results without controlling for time or individual effects, while Columns (2) and (3) include both, alongside additional control variables.

Table 4. Benchmark regression results.

Variable	**CEE**		
	(1)	**(3)**	**(3)**
DED	0.174 **	0.435 ***	0.369 ***
	(0.085)	(0.196)	(0.105)
ED	0.547 **	−5.842 ***	−0.699 ***
	(0.220)	(0.692)	-(0.151)
ED^2	−0.026 **	0.224 ***	0.025 ***
	(0.010)	(0.028)	(0.006)
IS	−0.075	2.505 **	0.474 **
	(0.072)	(0.839)	(0.159)
GI	−0.215 **	−0.653 ***	−0.221 ***
	(0.093)	(0.292)	(0.093)
PD	−0.000	−0.001 *	−0.000
	(0.000)	(0.000)	(0.000)
Constant	−1.889	−56.768 **	15.001 *
	(1.217)	(18.914)	(8.554)
Year FE	No	Yes	Yes
Provincial FE	No	No	Yes
Cities FE	No	Yes	No
Year × City FE	No	Yes	No
Year × provincial FE	No	No	No
N	2237	2236	2236
R	0.022	0.273	0.109

Note: T values are in parentheses. Standard deviation is presented as a cluster-robust standard error. ***, **, and * represent significance at 1%, 5%, and 10% statistical levels, respectively.

The coefficient of DED remains significantly positive across all model specifications, with values ranging from 0.174 to 0.435 and significance at 1% or 5% levels. This result indicates that digital economy development (DED) effectively promotes carbon emission efficiency (CEE). Quantitatively, based on the preferred specification in Column (3), a one-standard-deviation increase in DED leads to approximately a 3.7% improvement in CEE, highlighting a substantial and economically meaningful effect. This result confirms Hypothesis 1, suggesting that as digital technologies diffuse across sectors, they enhance production efficiency, optimize resource allocation, and facilitate energy conservation and emission reduction. Moreover, DED can indirectly affect domestic financial development and improvements in industrial structure, thereby improving the domestic CEE to a certain degree [35].

We analyzed the estimation results of the controlling variables shown in Table 4. After considering fixed effects, the coefficient of ED is negative, and the *p*-value is smaller than 0.01, which is notable at a 1% level of significance. This result indicates that under continual growth of the economy and continuous improvement of the per capita GDP, CEE is constantly decreasing, suggesting that development at this stage has not solved the dilemma of high energy consumption and pollution.

The coefficient of the square term of ED is positive, and the *p*-value is smaller than 0.01, with a significance level of 1%. This result reveals that China's CEE and economic growth present a U-shape change at this stage and that future economic development and the ecological environment can be simultaneously improved to a certain extent. Improvements to the level of economic development have an effect of first inhibiting and then promoting carbon emission efficiency.

The coefficient of IS for a fixed year and province is positive, and the *p*-value is smaller than 0.05, indicating a very positive result at a significance level of 5%. The coefficient of

IS for a fixed year and city is also positive, and the *p*-value is smaller than 0.05, indicating a significantly negative result at a 5% level. These analyses reveal that CEE is related to changes in industrial structure and that it is essential to adjust and support the industrial structure to improve CEE.

The coefficient of GI for a fixed year and province is negative, with a *p*-value smaller than 0.01, indicating a significantly negative result at a 1% level of significance. The coefficient of GI for a fixed year and city is positive, with a *p*-value less than 0.01, indicating a notably positive result at a 1% significance level. At the provincial level, CEE appears to be negatively correlated with government intervention, while at the level of cities, CEE is positively correlated with government intervention. This result indicates that government intervention and CEE differ based on the level of government. To improve CEE, we should reduce government intervention at the provincial level and further strengthen regulations for grassroots governments.

The coefficient of PD is negative when the year and province are fixed, but the results are insignificant. The coefficient of PD for a fixed year and city is positive, with a *p*-value less than 0.1, indicating a significantly negative result at a 10% level of significance. This result shows that population density and CEE change in opposite directions, with a significant negative correlation. According to this research, in the process of continually increasing the size of the city, an increase in population density also increases the consumption of natural resources, which reduces CEE. This result verifies Hypothesis 1.

4.3. Mechanism Analysis

DED plays a vital role in improving CEE. This research explores how DED affects CEE from the perspectives of the technological innovation level, financial development, foreign investment, etc. In this research, a mechanism effect model is established, with the evaluation outcomes shown in Table 5.

Table 5. Evaluation results for the action mechanism of DED level on CEE.

Variables	TIL (1)	FDL (2)	FDI (3)
DED	0.016 *	0.479 ***	4.555 ***
	(0.09)	(0.132)	(0.734)
Constant	3.372 ***	−41.897 ***	180.11 ***
	(0.889)	(13.505)	(70.897)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes
Year × Provincial FE	Yes	Yes	Yes
N	2236	2236	2236
R-sq	0.509	0.532	0.704

Note: T values are in parentheses. Standard deviation is presented as a cluster-robust standard error. ***, and * represent significance at 1%, and 10% statistical levels, respectively.

This study explored the mechanisms by which DED acts on CEE. Table 5 shows the evaluation results. The control variable selection was consistent with the benchmark regression, but the results are not listed. Column (1) in Table 5 shows the impact of DED on the technological innovation level. The estimation results indicate that the impact of DED on the technological innovation level is significant at a statistical level of 5%. There is also a positive correlation between DED and the input of technological innovation, demonstrating that DED can facilitate the input of technological innovation. The DE has become a new engine driving technological innovation [20], which is an effective way for information infrastructure to promote GHG emission performance [35]. Increasing investments in

technological innovation can improve economic development and reduce carbon intensity via technological progress, thereby improving the CEE of the DE. Therefore, increasing technological innovation is one of the avenues for DED to promote improvements in CEE.

Column (2) shows the influence of DED on financial development. The evaluation results indicate that the impact of DED on financial development is significant at a statistical level of 1%. DED is positively correlated with financial development, demonstrating that DED can drive financial development. The DE is of great value to financial development [48], leading to increased support for environmental investments and improvements to CEE. These research conclusions are consistent with those of Dong et al. (2022) [35], who found that financial development plays an intermediary role between DE and CE. To achieve their dual carbon targets, governments should follow the development of digital financial inclusion. Column (3) shows the influence of DED on foreign investment. The estimation outcomes indicate that the impact of DED on foreign investment occurs at a 1% level of significance. Here, DED is positively correlated with foreign investment, showing that DED can attract foreign investment. More broadly, the development of digital technology is having an increasing influence on global investment flows [49]. FDI has positive impacts on CE under certain financial development indicators [50]. Therefore, if China seeks to use DED to improve CEE, it should accelerate the attraction of foreign direct investment into the Chinese economy under the conditions of DE development.

According to our analysis, when TIL, FDL, and FDI are used as mechanism variables, the mechanism effect is significant. Therefore, DED can promote TIL, facilitate FDL, and increase the utilization degree of FDI to indirectly affect the role of the DE on CE. The above results support Hypothesis 2.

4.4. Robustness Test

We applied several methods to test the robustness of the conclusion and avoid the occasional phenomenon caused by the selection of specific variables in the empirical results, as shown in Table 6. First, technological innovation contributes to enhancing competitiveness and sustainable development [24], and improvements to CEE emerge from technological progress [51]. The scale efficiency of carbon emission also has a positive effect on reducing CE [52]. In addition, there is a strong correlation between CEE and the intensity of CE. For those reasons, we replaced the explanatory variable of CEE with carbon emission technical efficiency (CTE) and carbon emission scale efficiency (CSE) as the alternative variables of the CEE index, before conducting a robustness test. The outcomes reveal that the core explanatory variables are still significant, i.e., the core conclusion does not change substantially due to changes in CE measurement index. Although the alternative variables and explanatory variables have slight differences in parameter estimates, the positive and negative signs of the parameter estimates do not change and are both significant at a significance level of 1%. Additionally, the model's goodness of fit is similar.

Based on the existing experience and the robustness testing methods of Xie and Li (2021) [53], subsequent data processing was carried out for further robustness testing. We processed the data for three cases: (1) Winsorization, (2) estimation after deleting the provincial capital city, and (3) deletion of the 28 areas with serious pollution, which enabled us to consider environmental regulations. Columns (3), (4), and (5) show the relevant results. Here, we find that the DE can promote CEE at a significance level of 1%. Therefore, the core conclusion is not disturbed by outliers and verifies the robustness of the benchmark regression results.

Table 6. Results of the robustness test.

Variable	Alternative Explanatory Variable		Winsorization	Delete the Provincial Capital	Implement Environmental Regulation	Endogeneity Test
	CTE	CSE	CEE	CEE	CEE	CEE
	(1)	(2)	(3)	(4)	(5)	(6)
DED	0.154 ***	0.155 ***	0.598 ***	0.799 ***	0.348 ***	0.209 ***
	(0.039)	(0.043)	(0.121)	(0.184)	(0.105)	(0.035)
Constant	3.879	7.864	−22.402 ***	−111.49 ***	−88.743 **	11.988 **
	(3.400)	(3.455)	(6.546)	(21.798)	(28.247)	(1.394)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes	Yes	No
Cities FE	No	No	No	No	No	Yes
Year × Provincial FE	Yes	Yes	Yes	Yes	Yes	No
N	2236	2236	2030	1998	2013	2236
R	0.082	0.081	0.124	0.129	0.109	0.109
AR(1)						0.000
AR(2)						0.321
Hansen test						0.000

Note: T values are in parentheses. Standard deviation is presented as a cluster-robust standard error. *** and ** represent significance at 1% and 5% statistical levels, respectively.

In addition, we employed the system GMM method to test the endogeneity of digital economy development (DED) on carbon emission efficiency (CEE). As shown in column (6), after introducing all control variables and fixed effects, the coefficient of DED remains significantly positive at a 1% level, with an estimated value of 0.209. The results of the AR(1) and AR(2) tests indicate that the residual term exhibits first-order autocorrelation but no second-order autocorrelation (AR(1) $p < 0.1$, AR(2) $p > 0.1$), confirming the validity of the instrumental variables. Moreover, the Hansen test passes the over-identification restriction, further supporting the rationality of the selected instruments and the robustness of the model specification. Overall, the results demonstrate that the positive effect of DED on CEE remains stable and significant after addressing potential endogeneity concerns.

4.5. Heterogeneity Test

For the heterogeneity test, we narrowed the sample value range from nationwide to the eastern, central, western, and northeast regions. Table 7 presents the estimation results.

Table 7. Results of the regional heterogeneity test.

Variable	Eastern	Central	Western	Northeast
DED	0.201 **	2.485 **	0.284 ***	0.294
	(0.091)	(0.941)	(0.092)	(0.592)
Constant	−7.379	−247.30 **	−88.534 ***	−44.12
	(7.338)	(64.132)	(11.573)	(23.931)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Provincial FE	Yes	Yes	Yes	Yes
Year × Provincial FE	Yes	Yes	Yes	Yes
N	798	707	469	262
R-sq	0.086	0.192	0.167	0.075

Note: T values are in parentheses. Standard deviation is presented as a cluster-robust standard error. *** and ** represent significance at 1% and 5% statistical levels, respectively.

Table 7 shows the results after dividing the value samples into eastern, central, western, and northeastern areas. The main observation variable, i.e., the digital economic development index, is most significant for the western region, followed by the eastern and central regions; however, the effect is not significant for the northeast region. The positive and negative signs of the estimated parameter values do not change, possibly because the industrial structures of most cities in northeast China are still dominated by heavy chemical-resource-intensive industries, and the development of the DE is relatively limited. The resulting DE did not have a significant effect on the CEE of these cities [54]. In addition, the long-standing industrial legacy, aging population structure, and sustained population decline in the northeast have also constrained the region's capacity for digital transformation and innovation diffusion. These demographic and structural challenges weaken the driving force of the digital economy for green and low-carbon transition, leading to insignificant empirical results [55]. Thus, the DED in the eastern, central, and western regions promotes improvements in CEE, but the degree of improvement is more obvious in the central region than the eastern region. Based on the national regional economic development strategy, the western region benefits from a late-mover advantage with the help of DE, thus breaking through the traditional allocation of factors and resources and narrowing the "digital divide" between the eastern and central regions while rapidly improving CEE. Therefore, the impact trend of DED on China's CEE has strong regional heterogeneity.

Table 8 shows the test results after the sample is divided into resource-based and non-resource-based cities. For resource-based cities, the development index of the DE is positively correlated with CEE, with significance at a 1% level. For non-resource-based cities, the development index of the DE is positively correlated with CEE, which is significant at a level of 5%. Although DED has a significant promotion effect on CEE for both resource-based and non-resource-based cities, the promotion effect in resource-based cities is stronger. In the process of development, resource-based cities can make full use of local resource advantages, organically combine local traditional industries with DE, and realize local DED by optimizing their industrial structures and relieving their energy intensities [56], thus effectively promoting CEE. The above results support Hypothesis 3.

Table 8. Heterogeneity test results for resource-based and non-resource-based cities.

Variable	Resource-Based City	Non-Resource-Based City
DED	1.504 **	0.212 ***
	(0.764)	(0.063)
Constant	−125.808 ***	6.524
	(45.035)	(6.635)
Control variables	Yes	Yes
Year FE	Yes	Yes
Provincial FE	Yes	Yes
Year × Provincial FE	Yes	Yes
N	891	1345
R-sq	0.168	0.091

Note: T values are in parentheses. Standard deviation is presented as a cluster-robust standard error. *** and ** represent significance at 1% and 5% statistical levels, respectively.

5. Conclusions and Limitations

5.1. Conclusions

Based on panel data from 283 Chinese cities from 2011 to 2018, this study empirically examined the influence of China's digital economy development (DED) on urban carbon emission efficiency (CEE), its regional heterogeneity, and its underlying mechanisms. The main conclusions are as follows.

First, DED is an important factor to promote CEE, which has an obvious effect on the process of realizing China's dual carbon target. In addition, CEE is positively correlated with industrial structural change and negatively correlated with population density. The impact of CEE, moreover, differs under different levels of government. Therefore, with the rapid development of China's DE, China's CEE indicates an obvious upward trend.

Second, the effects of DED on CEE exhibit significant regional heterogeneity. The impact is strongest in western China, followed by that in the eastern and central regions. After accounting for resource endowment, DED was found to have a significantly positive impact on CEE in resource-based cities, while the effect was weaker or negative in non-resource-based cities.

Finally, by exploring the influence mechanism of DED on CEE, we found that the technological innovation level is one of the avenues through which DED promotes improvements to CEE. Increasing financial development and foreign direct investment can also indirectly improve the CEE of DED.

5.2. Research Limitations and Future Directions

Despite its contributions, this study has several limitations that suggest avenues for future research. The analysis period (2011–2018), for example, does not capture the most recent digital-economy expansion, especially the rapid post-COVID digitalization wave. This limitation mainly arises from the lack of consistent and comparable city-level carbon emission data after 2018, as subsequent data released by different statistical departments and research institutions vary in their estimation methods and boundary definitions, making long-term comparability difficult. Future work could extend the dataset to more recent years as reliable data become available and employ dynamic panel or spatial econometric models to better reflect new digital–low-carbon development trends. Meanwhile, the measurement of DED and CEE, though comprehensive, may still omit emerging digital indicators such as data-asset valuation, AI application intensity, or digital-platform penetration. Future studies could incorporate these factors to improve index precision and reflect the evolving characteristics of the digital economy.

6. Policy Implications

Based on the above findings, we propose the following policy recommendations. First, we should accelerate the comprehensive development of the digital economy and deepen its integration with low-carbon transition. Government departments should formulate integrated digital–low-carbon development plans and improve top-level coordination mechanisms across sectors such as industry, energy, and the environment. Efforts should be made to accelerate the industrialization and market application of digital technologies—including big data, artificial intelligence, and cloud computing—to enhance energy efficiency and optimize industrial processes. For traditional energy-intensive industries, regulatory agencies can establish pilot programs for digital upgrading and promote the use of digital-twin systems, smart energy management, and carbon-footprint tracking platforms. These measures will improve overall resource utilization efficiency and enhance carbon emission efficiency (CEE) through the application of digital economy development (DED).

Second, we should implement regionally differentiated development strategies and strengthen interregional collaborative mechanisms. In the eastern region, governments should focus on the deep integration of digital innovation and high-end industrial chains, cultivating green digital clusters and fostering international competitiveness through innovation incentives and regulatory sandboxes. The central region should emphasize industrial digital transformation and energy structure optimization, guided by digital infrastructure construction and regional innovation centers. The western region, which showed the

strongest marginal effect of DED on CEE, should leverage its resource base to develop new models of green growth—such as digital mining, clean-energy digital platforms, and carbon-data monitoring systems—supported by interregional cooperation mechanisms with the east. Government agencies should also establish cross-regional coordination frameworks for data sharing, technology transfer, and carbon trading to leverage comparative advantages and facilitate a coordinated national low-carbon transition.

Third, we should refine digital governance and policy support mechanisms to strengthen the role of technological innovation and capital guidance. The government should increase its investments in low-carbon technology innovation through fiscal subsidies, tax incentives, and other policy tools to encourage corporate green R&D. At the same time, green finance and foreign direct investment (FDI) policies should prioritize low-carbon digital industries. Establishing green investment funds, carbon-credit markets, and risk-compensation mechanisms can guide private capital toward digital low-carbon projects. These measures will help amplify the intermediary effects of DED through technological progress, financial development, and foreign investment, thereby systematically enhancing carbon emission efficiency.

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References

1. Yang, J.; Dong, H.H.; Jiang, T.Y. Structural emission reduction in China's industrial systems and energy systems: An input-output analysis. *Environ. Sci. Pollut. Res.* **2022**, *29*, 6010–6025. [CrossRef]
2. Li, J.; Wang, Q.M. Impact of the Digital Economy on the Carbon Emissions of China's Logistics Industry. *Sustainability* **2022**, *14*, 8641. [CrossRef]
3. Zhang, W.; Liu, X.M.; Wang, D.; Zhou, J.P. Digital economy and carbon emission performance: Evidence at China's city level. *Energy Policy* **2022**, *165*, 112927. [CrossRef]
4. Clifton, N.; Füzi, A.; Loudon, G. Coworking in the Digital Economy: Context, Motivations, and Outcomes. *Futures* **2019**, *135*, 102439. [CrossRef]
5. Zhang, M.L.; Liu, Y. Influence of digital finance and green technology innovation on China's carbon emission efficiency: Empirical analysis based on spatial metrology. *Sci. Total Environ.* **2022**, *838 Pt 3*, 156463. [CrossRef]
6. Du, K.R.; Li, J.L. Towards a green world: How do green technology innovations affect total-factor carbon productivity. *Energy Policy* **2019**, *131*, 240–250. [CrossRef]
7. Ma, Q.; Khan, Z.; Tariq, M.; IŞik, H.; Rjoub, H. Sustainable digital economy and trade adjusted carbon emissions: Evidence from china's provincial data. *Econ. Res. Ekon. Istraživanja* **2022**, *35*, 5469–5485. [CrossRef]
8. Aydin, E.; Eichholtz, P.; Yönder, E. The economics of residential solar water heaters in emerging economies: The case of Turkey. *Energy Econ.* **2018**, *75*, 285–299. [CrossRef]
9. Li, Y.; Yang, X.; Ran, Q.; Wu, H.; Irfan, M.; Ahmad, M. Energy structure, digital economy, and carbon emissions: Evidence from china. *Environ. Sci. Pollut. Res.* **2021**, *28*, 64606–64629. [CrossRef]

10. Zhou, J.; Lan, H.L.; Zhao, C.; Zhou, J.P. Haze pollution levels, spatial spillover influence, and impacts of the digital economy: Empirical evidence from china. *Sustainability* **2021**, *13*, 9076. [CrossRef]
11. Zhong, R.X.; He, Q.; Qi, Y.B. Digital Economy, Agricultural Technological Progress, and Agricultural Carbon Intensity: Evidence from China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 6488. [CrossRef]
12. Lin, B.; Zhou, Y. Does the Internet development affect energy and carbon emission performance? *Sustain. Prod. Consum.* **2021**, *28*, 1–10. [CrossRef]
13. Zheng, H.H.; Li, X. The impact of digital financial inclusion on carbon dioxide emissions: Empirical evidence from Chinese provinces data. *Energy Rep.* **2022**, *8*, 9431–9440. [CrossRef]
14. Sheng, P.F.; Li, J.; Zhai, M.X.; Majeed, M.U. Economic growth efficiency and carbon reduction efficiency in china: Coupling or decoupling. *Energy Rep.* **2021**, *7*, 289–299. [CrossRef]
15. Sheng, P.; Zhai, M.; Zhang, Y.; Kamal, M.A. The effects of urbanization on household wastewater emissions in china: Efficient- and inefficient- emissions. *Environ. Pollut.* **2020**, *267*, 115350. [CrossRef]
16. Du, Q.; Deng, Y.G.; Zhou, J.; Wu, J.; Pang, Q.Y. Spatial spillover effect of carbon emission efficiency in the construction industry of China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 2466–2479. [CrossRef]
17. Zhang, W.; Zhu, Z.R.; Liu, X.M.; Cheng, J. Can green finance improve carbon emission efficiency? *Environ. Sci. Pollut. Res.* **2022**, *29*, 68976–68989. [CrossRef]
18. Li, L.S.; Cai, Y.; Liu, L. Research on the Effect of Urbanization on China's Carbon Emission Efficiency. *Sustainability* **2020**, *12*, 163. [CrossRef]
19. Chen, L.; Liu, Y.; Gao, Y.; Wang, J.J. Carbon Emission Trading Policy and Carbon Emission Efficiency: An Empirical Analysis of China's Prefecture-Level Cities. *Front. Energy Res.* **2021**, *9*, 793601. [CrossRef]
20. Ding, C.H.; Liu, C.; Zheng, C.Y.; Li, F. Digital Economy, Technological Innovation and High-Quality Economic Development: Based on Spatial Effect and Mediation Effect. *Sustainability* **2022**, *14*, 216. [CrossRef]
21. Wang, H.; Hu, X.; Ali, N. Spatial Characteristics and Driving Factors Toward the Digital Economy: Evidence from Prefecture-Level Cities in China. *J. Asian Financ. Econ. Bus.* **2022**, *9*, 419–426.
22. Chen, X.H.; Yan, D.; Chen, W. Can the digital economy promote Fintech development? *Growth Change* **2022**, *53*, 221–247. [CrossRef]
23. Li, Z.H.X.; Li, N.Y.; Wen, H.W. Digital Economy and Environmental Quality: Evidence from 217 Cities in China. *Sustainability* **2021**, *13*, 8058. [CrossRef]
24. Li, J.L.; Cen, L.T.; Chen, Y.; He, J.W. Digital economy, technological innovation, and green economic efficiency—Empirical evidence from 277 cities in China. *Manag. Decis. Econ.* **2022**, *43*, 616–629. [CrossRef]
25. Zhang, J.; Lyu, Y.; Li, Y.; Geng, Y. Digital economy: An innovation driving factor for low-carbon development. Environ. Impact Asses. *Rev.* **2022**, *96*, 106821.
26. Liu, Y.; Yang, Y.L.; Li, H.H.; Zhong, K.Y. Digital Economy Development, Industrial Structure Upgrading and Green Total Factor Productivity: Empirical Evidence from China's Cities. *Int. J. Environ. Res. Public Health* **2022**, *19*, 2414. [CrossRef]
27. Li, Z.G.; Wang, J. The Dynamic Impact of Digital Economy on Carbon Emission Reduction: Evidence City-level Empirical Data in China. *J. Clean. Prod.* **2022**, *351*, 131570. [CrossRef]
28. Zhang, R.J.; Tai, H.W.; Cheng, K.T.; Zhu, Y.T.; Hou, J.J. Carbon emission efficiency network formation mechanism and spatial correlation complexity analysis: Taking the Yangtze River Economic Belt as an example. *Sci. Total Environ.* **2022**, *841*, 156719. [CrossRef]
29. Meng, F.S.; Zhao, Y. How does digital economy affect green total factor productivity at the industry level in China: From a perspective of global value chain. *Environ. Sci. Pollut. Res.* **2022**, *29*, 79497–79515. [CrossRef]
30. Dong, F.; Li, Y.F.; Qin, C.; Zhang, X.Y.; Chen, Y.H.; Zhao, X.; Wang, C. Information infrastructure and greenhouse gas emission performance in urban China: A difference-in-differences analysis. *J. Environ. Manag.* **2022**, *316*, 115252. [CrossRef]
31. Wang, L.; Chen, Y.Y.; Ramsey, T.S.; Hewings, G. Will researching digital technology really empower green development? *Technol. Soc.* **2021**, *66*, 101638. [CrossRef]
32. Su, C.W.; Xie, Y.N.; Shahab, S.; Faisal, C.M.N.; Hafeez, M.; Qamri, G.M. Towards Achieving Sustainable Development: Role of Technology Innovation, Technology Adoption and CO2 Emission for BRICS. *Int. J. Environ. Res. Public Health* **2021**, *18*, 277. [CrossRef]
33. Zhong, K.M.; Fu, H.Y.; Li, T.H. Can the Digital Economy Facilitate Carbon Emissions Decoupling? An Empirical Study Based on Provincial Data in China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 6800. [CrossRef]
34. Han, D.R.; Ding, Y.Y.; Shi, Z.Y.; He, Y. The impact of digital economy on total factor carbon productivity: The threshold effect of technology accumulation. *Environ. Sci. Pollut. Res.* **2022**, *29*, 55691–55706. [CrossRef]
35. Dong, F.; Hu, M.Y.; Gao, Y.G.; Liu, Y.J.; Zhu, J.; Pan, Y.L. How does digital economy affect carbon emissions? Evidence from global 60 countries. *Sci. Total Environ.* **2022**, *852*, 158401. [CrossRef]

36. Jia, L.J.; Hu, X.L.; Zhao, Z.W.; He, B.; Liu, W.M. How Environmental Regulation, Digital Development and Technological Innovation Affect China's Green Economy Performance: Evidence from Dynamic Thresholds and System GMM Panel Data Approaches. *Energies* **2022**, *15*, 884. [CrossRef]
37. Xu, Q.; Zhong, M.R.; Cao, M.Y. Does digital investment affect carbon efficiency? Spatial effect and mechanism discussion. *Sci. Total Environ.* **2022**, *827*, 154321.
38. Dai, S.; Tang, D.; Li, Y.; Lu, H. Digital trade, trade openness, FDI, and green total factor productivity. *Int. Rev. Financ. Anal.* **2025**, *97*, 103777. [CrossRef]
39. Liao, C. Impact of green finance on carbon emission efficiency and spatial spillover effects: A case study of Guangzhou, China. *Sustainability* **2024**, *16*, 10309. [CrossRef]
40. Hao, W.; Ye, S.; Zhang, Y. The impact of digital finance on regional carbon emission reduction capacity from the perspective of resource misallocation: Evidence from Chinese cities. *Sustain. Futures* **2025**, *10*, 100961. [CrossRef]
41. Che, S.; Wang, J. Digital economy development and haze pollution: Evidence from China. *Environ. Sci. Pollut. Res.* **2022**, *48*, 73210–73226. [CrossRef]
42. Wang, J.L.; Wang, W.L.; Ran, Q.Y.; Irfan, M.; Ahmad, M. Analysis of the mechanism of the impact of internet development on green economic growth: Evidence from 269 prefecture cities in China. *Environ. Sci. Pollut. Res.* **2022**, *29*, 9990–10004. [CrossRef]
43. Cheng, J.X.; Xu, L.; Wang, H.X.; Geng, Z.F.; Wang, Y.M. How does the marginal abatement cost of CO2 emissions evolve in Chinese cities? An analysis from the perspective of urban agglomerations. *Sustain. Prod. Consum.* **2022**, *32*, 147–159. [CrossRef]
44. Liu, Y.; Feng, C. What drives the fluctuations of "green" productivity in China's agricultural sector? A weighted Russell directional distance approach. *Resour. Conserv. Recycl.* **2019**, *147*, 201–213. [CrossRef]
45. Yang, L.S.; Ni, M.Y. Is financial development beneficial to improve the efficiency of green development? Evidence from the "Belt and Road" countries. *Energy Econ.* **2022**, *105*, 105734. [CrossRef]
46. Cole, M.A.; Elliott, R.J.; Shimamoto, K. Industrial characteristics, environmental regulations and air pollution: An analysis of the UK manufacturing sector. *J. Environ. Econ. Manag.* **2005**, *50*, 121–143. [CrossRef]
47. Sun, W.; Huang, C. How does urbanization affect carbon emission efficiency? Evidence from China. *J. Clean. Prod.* **2020**, *272*, 122828. [CrossRef]
48. Sydorovych, O.; Perchuk, O.; Fedyk, M.; Klymenko, S.; Matviy, I.; Chupryna, L.; Igor Yaremko, I. Digitization of the Financial System in the World Economy. *Int. J. Comput. Sci. Netw. Secur.* **2021**, *21*, 611–619.
49. Bogoviz, A.V.; Lobova, S.V.; Ragulina, J.V. Shift of the Global Investment Flows in the Conditions of Formation of Digital Economy. In *The Future of the Global Financial System: Downfall or Harmony*; Popkova, E., Ed.; ISC 2018 Lecture Notes in Networks and Systems 57; Springer: Cham, Switzerland, 2019.
50. Liu, W.L.; Khan, H.; Khan, I.; Han, L. The impact of information and communication technology, financial development, and energy consumption on carbon dioxide emission: Evidence from the belt and road countries. *Environ. Sci. Pollut. Res.* **2022**, *29*, 27703–27718. [CrossRef]
51. Li, W.W.; Wang, W.P.; Gao, H.W.; Zhu, B.Q.; Gong, W.F.; Liu, Y.C.; Qin, Y. Evaluation of regional metafrontier total factor carbon emission performance in china's construction industry: Analysis based on modified non-radial directional distance function. *J. Clean. Prod.* **2020**, *256*, 120425. [CrossRef]
52. Sun, W.; Huang, C.C. Predictions of carbon emission intensity based on factor analysis and an improved extreme learning machine from the perspective of carbon emission efficiency. *J. Clean. Prod.* **2022**, *338*, 130414. [CrossRef]
53. Xie, W.C.; Li, X. Can Industrial Agglomeration Facilitate Green Development? Evidence From China. *Front. Environ. Sci.* **2021**, *9*, 745465. [CrossRef]
54. Guo, Y.H.; Tong, L.J.; Mei, L. The effect of industrial agglomeration on green development efficiency in Northeast China since the revitalization. *J. Clean. Prod.* **2020**, *258*, 120584. [CrossRef]
55. Guo, D.; Li, L.; Pang, G. Does the integration of digital and real economies promote urban green total factor productivity? Evidence from China. *J. Environ. Manag.* **2024**, *370*, 122934. [CrossRef] [PubMed]
56. Zhang, H.T.; Sun, X.M.; Bi, C.F.; Ahmad, M.; Wang, J. Can sustainable development policy reduce carbon emissions? Empirical evidence from resource-based cities in China. *Sci. Total Environ.* **2022**, *838*, 156341. [CrossRef]

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